In the Aftermath of Large Natural Disasters, what happens to foreign aid?

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Abstract

We examine Official Development Assistance (ODA) in the aftermath of large natural disasters in developing countries between 1970 and 2008. We find that while ODA increases significantly compared to pre-disaster flows, the typical surges are small in relation to the size of the affected economies or the estimated economic damages. Moreover, we find that the size of the surges is related to the catastrophic nature of the event itself and the lack of other resources available to the affected countries. However, we do not find robust evidence that political affinity between donors and affected countries, and common geo-strategic interests, matter for the allocation of post disaster aid.

Keywords: Natural Disasters, Foreign Aid, Official Development Assistance (ODA), event study.

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1. Introduction

Human and economic catastrophes that are associated with natural hazards are obviously not new; even if new media has changed the way we are aware of them. The January 2010 earthquake in Haiti and the Indian Ocean tsunami of 2004 both generated much international media attention and unprecedented amounts of international flows of aid from private charities, non-governmental organizations (NGOs), governments, and multilateral organizations. According to the United Nation's ReliefWeb, $6.2 billion dollars were pledged for relief in the countries affected by the Indian Ocean tsunami and $3.3 billion dollars were pledged for relief in Haiti.[1] But pledges made while media attention is at its peak may not always be disbursed, may take a long time to arrive, or may replace previously pledged aid. We start by asking: how much does foreign aid really increase following a catastrophic natural disaster?

As far as we could find, no one has ever looked at this question systematically, in spite of its obvious importance. The main stumbling block is that data sources that describe emergency international assistance (in particular the United Nations' Financial Tracking Service database) do not compare their information to disbursements prior to the event, so that it may be that much of these resources would have been provided anyway (i.e., without a disaster occurring).[2]

[1] http://fts.unocha.org/ (accessed 9/10/2010).
[2] It is a well established fact that poor countries, the usual recipients of foreign aid, are disproportionally affected by natural disasters (see Cavallo and Noy, 2010).

We present several event study estimates of the actual surge in aid flows that affected countries experienced following large natural disasters. Our results suggest a mixed picture: while foreign aid –Official Development Assistance (ODA) — typically increase significantly relative to the pre-disaster flows, the nominal dollar amounts are usually small compared to the size of the economies and the actual estimated direct economic damages caused by the events.

After calculating the aid surges following past disasters, we examine the determinants of these surges. Besides obvious determinants of the size of the post-disaster aid inflows, such as the magnitude of the disaster, there are other interesting hypotheses we examine. We find that bigger and richer countries –conceivably with more resources available to be re-directed toward reconstruction – receive less foreign aid in the aftermath of natural disasters, and similarly, countries with larger stocks of international foreign reserves –i.e., more resources available to use for importing capital goods to facilitate reconstruction— also are given less aid. More media reporting of a disaster generates more aid inflows, although media attention is largely correlated to the severity of the event. Initial pre-disaster international humanitarian support reduces post-disaster aid inflows. Finally, we do not find evidence that supports the commonly-held view that political/cultural affinity between donors and affected countries, and geo-political interests drive donor behavior following catastrophic natural events. Based on these findings, we conjecture that countries facing large natural disasters losses should not expect foreign aid flows to cover a large proportion of the hefty toll that these events usually impose upon impact.

The structure of the paper is as follows: we first review the related literature in order to place our contribution in context. Next, we discuss the data and introduce some stylized facts on post disaster aid flows based on an event study approach. We then explore the determinant of aid surges using a cross section of events. Finally, we conclude with discussion and topics for further research.

2. The Literature on Emergency International Assistance

Since there is not much research on emergency post-disaster aid, most of the research described in this section focuses on foreign assistance more generally. Few papers, however, do examine post-natural-disasters aid flows. Yang (2008) uses hurricane intensity data and concludes that official foreign aid increases significantly after disasters – for the developing countries in his sample, 73% of disaster damages are ultimately covered by aid inflows.[3] David (2010) examines a similar question but with a different empirical approach and includes data on other types of disasters besides hurricanes. He finds that aid does not seem to increase after climatic disasters and their increase following geological ones is delayed and very small. This divergence in results suggests the need to revisit the question using a larger sample of countries and events and different methods. [4]

Strömberg (2007) is largely interested in answering two questions: (1) Whether the amount of aid given after a disaster is influenced by news coverage of the disaster (the answer: yes); and (2) Whether a potential donor country is more likely to give aid if it has established a

[3] Yang's sample is concentrated on a few island nations, the countries of Central America, and two big countries that frequently experience storm damage, Bangladesh and the Philippines.
[4] Both papers attempt to estimate the impact of disasters on financial flows more generally,

previous connection with the affected country[5] (the answer is again: yes). Besides providing quantitative answers to these questions, Strömberg (2007) provides no other assessment of post-disaster foreign assistance. In our work, we both calculate the aid surge (i.e., control for aid that would have anyway been provided as per past practice) and estimate other determinants of this aid surge in order to better predict future post-disaster aid.

Another factor flagged as important in determining foreign aid volume is geo-strategic interest (e.g., Olsen et al., 2003).[6] A surprisingly large number of papers focus on the politics of aid given by the United States, and most of these works also emphasize that geo-strategic and political interests play a large role in determining American aid allocations across space and over time (recent examples are Drury et al., 2005, and Fleck and Kilby, 2010); though others suggest a humanitarian motivation is also evident (e.g., Demirel-Pegg and Moskowitz, 2009).[7] Bobba and Powell (2007) presents empirical evidence that suggest that aid that is dictated by political and geo-strategic interests is less effective in generating economic growth. We explore whether these political and strategic considerations are important determinants of the foreign aid that is disbursed in the aftermath of large natural disasters as well.

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[5] This relationship can be a colonial history, extensive trade relations, geographical proximity, or shared culture/language.

[6] While not focusing on disaster aid *per se*, Alesina and Dollar (2000) emphasize similar political and geo-strategic considerations. Fink and Redaelli (2009) use a different dataset than Strömberg (2007) and like Olsen et al. (2003) emphasize political factors guiding aid allocations.

[7] Two additional papers develop the 'political motivation' argument using different micro datasets. Chong and Gradstein (2008) use data from the World Values Survey to show that satisfaction with own/donor government is a determinant of public support for and therefore of actual aid outflows. Raschky and Schwindt (2009), using data on specific post-disaster bilateral donations, analyze the political-economy reasons for donors' choices whether to channel the aid through a multilateral, and whether to provide aid as cash or in-kind. Powell and Bobba (2006) also examine the nature of the channel through which foreign aid is intermediated, but not in the context of post-disaster emergency assistance.

Frot and Santiso (2009) focus on another aspect of aid flows, herding.[8] They argue that, after disasters, herding is beneficial, but that herding among donors is common also when no negative shock, such as a disaster, has occurred. Their empirical work shows that this type of herding is indeed present in the data.[9]

Beyond these supply factors guiding aid allocations, Olsen et al. (2003) note that demand-factors (i.e., the receiving country's characteristics), and in particular its readiness to absorb new flows through NGOs, is important in determining aid inflows. On the other hand, they find little evidence that policy effectiveness by the receiving government, and the presence of efficient institutional capacity to implement aid, matter for the magnitude of aid donations (though this may vary by the nature of the donating source – see Easterly and Pfutze, 2008).

In work that is similar to ours in its approach even if the subject matter and specific empirical methodologies are different, Kang and Meernik (2004) examine the increase in aid following armed conflict.[10] They quantify the post-conflict surge in aid and attempt to explain the size of the surge by the nature of the conflict and the regime type that reigned at its end.

Besides the large literature on the efficacy of aid in general, several papers from the International Monetary Fund assess the consequences of large and sudden increases in aid flows on the receiving economies (International Monetary Fund, 2005 and references therein). This work does not associate aid surges with the occurrence of natural disasters, and in the five

[8] Fink and Redaelli (2009) call herding a 'bandwagon effect.'

[9] Herding that is not associated with large trigger events suggests possible inefficiencies that may explain some of the failure of aid more generally. For recent work on the effects of aid, see Easterly (2003) or more recently Rajan and Subramanian (2008) and Werker et al. (2009).

[10] They examine the determinants of these aid surges using an 11-year cross-country panel with a conflict binary variable.

case studies they examine the aid surge occurred because of other reasons. However, this research may suggest ways in which the aid surge that follows disasters may be better directed by the donors or utilized by the receiving government. Agénor and Aizenman (2010) add to this aid-surge literature, and argue, with the support of a theoretical model, that aid volatility potentially leads to poverty traps. In spite of this adverse risk imposed by aid volatility, they find that under certain conditions self-insurance (a contingency fund) that will ameliorate this volatility is sub-optimal since its existence distorts the donors' motivations.[11] This 'moral hazard' conclusion is relevant to our findings about the availabity of domestic resources (in particular foreign reserves) as an important determinant of the post-disaster aid allocations.

The last strand of the existing literature that is relevant to our endeavor is specific case studies that examine the experience of countries following large disasters with a focus on aid inflows.[12] The Asian tsunami of December, 2004, generated several research projects that examined the impact of post-tsunami aid. For example, Jayasuriya and McCawley (2008) examine the impact of aid flows in Sri Lanka, Indonesia and Thailand. Their work pays particular attention to the type and time-path of aid given and its specific impact on the construction sector – they point to the resulting escalating costs of reconstruction as an adverse consequence that should be mitigated through more gradual disbursement and implementation of aid projects.

[11] In contrast, Buffie et al. (2010) do not consider this moral hazard problem and conclude that optimal policy would be a partial saving of aid receipts –though they point out that most donors insist on full spending and absorption. Berg et al. (2010) reach similar conclusions

[12] For citations to other case studies that examine the economics of disasters but do not focus specifically on the post-disaster aid see Cavallo and Noy (2009). Many case studies do not focus on aid but do include observations regarding the magnitude and efficacy of aid that may be useful (e.g., Coffman and Noy, 2010). Much more research on disasters is available through www.preventionweb.net.

These papers suggest different hypotheses that are worthwhile examining within the context of post-disaster aid allocations. Our contribution is to emphasize a different (and we think more accurate) measure of post-disaster aid that we calculate based on the baseline aid flows that precede the disaster. Using this novel measure of post disaster aid-surges, we are able to shed more light both on the determinants of these aid flows and examine several hypotheses concerning these determinants.

3. Data

3.1 Disaster and Aid Data

Almost all the empirical work on natural disasters relies on the publicly available Emergency Events Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain, Belgium (http://www.emdat.be/). EM-DAT defines a disaster as a natural situation or event which overwhelms local capacity and/or necessitates a request for external assistance. For a disaster to be entered into the EM-DAT database, at least one of the following criteria must be met: (1) 10 or more people are reported killed; (2) 100 people are reported affected; (3) a state of emergency is declared; or (4) a call for international assistance is issued. Disasters can be hydro-meteorological**,** including floods, wave surges, storms, droughts, landslides and avalanches; geophysical, including earthquakes, tsunamis and volcanic eruptions; and biological, covering epidemics and insect infestations (the latter are very infrequent).

The disaster impact data reported in the EM-DAT database consists of direct damages (e.g., value of damage to infrastructure, crops, and housing in current dollars), the number of people killed, and the number of people affected.[13] As Cavallo and Noy (2009) observe, many of the events reported in this database are quite small and are unlikely to have any significant impact on aid disbursements and on the macro-economy more generally. We therefore limit our investigation to disasters in which the number of people killed is above the mean for the entire dataset (more on this below).[14]

Detailed data on aid flows is available from the Organization for Economic Cooperation and Development's Development Assistance Committee (OECD-DAC), and the United Nations' Financial Tracking Service (UN-FTS). The OECD-DAC data on official development assistance covers annual bilateral aid extended from 22 donors to a wide number of individual recipient countries. The UN-FTS database does not aggregate aid flows annually but rather presents information for each international humanitarian aid appeal issued by the UN. Many of these appeals correspond to natural disasters.

The UN-FTS datahas two advantages: First, it provides data for each appeal separately, hence allowing direct correspondence between aid flows and individual disasters. Second, the OECD-DAC focuses only on OECD governments and multilateral organizations, while the UN-FTS also tracks aid flows of private donors. However, UN-FTS data is based on donors' voluntary reporting and may significantly mis-estimate the volume of actual new aid given.

We choose to use the OECD-DAC data because of its more comprehensive nature and because it is based on actual disbursements rather than pledges or commitments. Thus, we can

[13] The measure for direct damages does not include indirect impacts due to the damage to physical infrastructure and productive capacity. Indirect damages can also be a consequence of the fact that reconstruction pulls resources away from normal production.

[14] The two other papers that are closest to ours in their interest use more lenient criteria for inclusion. Fink and Redaelli (2009) use a sample of 400 disasters in the last 15 years while Raschky and Schwindt (2009) use 228 disasters from 2000-2007.

directly estimate by how much foreign official aid increases in the aftermath of disasters instead of focusing on undisbursed pledges that may not materialize. Furthermore, while the OECD-DAC data does not separately measure post-disaster aid, the event study methodology we apply seeks to overcome that problem. By comparing aid flows before and after a natural disaster, we are able to calculate the actual aid surge from aid data we observe; we assume this aid surge is related only to the disaster itself.[15]

3.2 Descriptive Statistics on Aid and Disasters

There are a total of 6,530 events recorded in the EM-DAT database between January 1970 and June 2008, of which 3,097 (47.4%) are floods, 2,617 (40.1%) are storms, and 816 (12.5%) are earthquakes. Oftentimes there are multiple events recorded in a given country-year. In those cases, we add up the corresponding disaster magnitudes and define a "combined" disaster for that country-year observation.

Disasters are fairly common. Out of a total of 7,644 year-country observations (196 countries x 39 years), 2,597 (34%) meet the requirements to be designated as a natural disaster. However, as already noted, truly large events are less common. When we restrict the sample only to large events, and where “large” is defined to be larger than the world mean of 25.1 persons killed per million inhabitants, only 171 year-country observations remain.[16] We drop nine additional observations either because these coincided with another major event in the country that was more likely to have affected foreign aid (e.g. Afghanistan in 2002) or we

[15] It is possible that another event that had an impact on aid flows happened concurrently. However, since the specific timing of large natural disasters is largely unpredictable it seems reasonable to assume that our event study approach overcomes this problem in a large enough sample.
[16] To avoid overrepresentation of small countries, we exclude 46 very small events, defined as those with fewer than 10 people reported dead or missing and for which reported damages are less than 2009 US$ 10 million.

found some anomalies in the data (e.g. Turkey 1999).[17] Out of the remaining subset of events, only 138 have the full set of information required (particularly aid data in the OECD-DAC dataset) to do the event study we pursue here. This is the sample of events that we study.

In other words, an "event" in our sample is a country-year observation for which: i) there is record in the EM-DAT database of one or several natural disasters that hit the country on that year that caused at least as many fatalities as the world mean for the entire time period; ii) the disaster itself is not too small in absolute terms; iii) data is available to perform the analysis we conduct; and iv) the observation is not an obvious outlier.[18]

Table 1 presents summary statistics of the resulting sample. We calculate the medians of the consequence of the disasters (in terms of number of people killed and the direct economic damages), and medians for the data we constructed on post-disasters aid surges based on data taken from the OECD-DAC. We prefer to focus on the medians here because averages may be skewed by a few big outliers. An "aid surge" is computed as the difference of the average aid flows up to two years after the disasters and the average aid flows two years before.[19]

We further disaggregate events in three sub-samples. Sample 1 includes all of the disasters in the sample described above. Sample 2 excludes those disasters which overlapped with other identified events (any disaster that occurred within two years before or after another event was excluded). Sample 3 does include overlapping events but excludes

[17] Dropped events are Afghanistan (2002) – war in Afghanistan, Bangladesh (1973) – Post Independence process , Haiti (1994) – UN political intervention after the 1991 coup d'état , Iran (1972) – Several military conflicts, aid flows dropped by almost 70%, Saint Lucia (1980) – Saint Lucia's independence from United Kingdom , Turkey (1999) – historically low levels of aid (after disaster's aid-flows increased by almost 500%), Venezuela (1999) – historically low levels of aid in 1997 (aid after disaster increased almost by 200%).

[18] A list of these events is available in appendix table 1.

[19] Excluding the year of the disaster itself from the post event averages does not change the results.

observations in which there were multiple disasters in a given year and intensity data (i.e. number of killed people or economic damages data) was not available for at least one of them. Sample 1, our most comprehensive, includes 138 disasters, while the most restrictive sample, sample 2, includes only 79 disasters. For sample 1, the median mortality per disaster is 327 people, or 59.8 people killed per million inhabitants, median economic damage is 4.2% of GDP and the aid surge is 0.1% of GDP or an 18% increase in aid relative to pre-disaster aid flows. The numbers for the other samples are very similar.

In order to get a better understanding of the dynamics of post disaster foreign aid flows, Figure 1 presents the data on aid flows in the years before and after the disasters in our samples. The figures are standardized so that the average of pre-disaster aid inflows is defined as 1. Aid flows appear to increase already in the year of the disaster (by 20% for sample 1) and then increase further in the year after the disaster by about 40% (for samples 1 and 3 and about 55% for sample 2). While aid flows dips somewhat in the second year after the disaster, they do not revert back to their pre-disaster levels in the 6 years we track following the disaster.

Taken together, these results suggest that official foreign aid increases in the aftermath of large natural disasters and they do not revert back to pre-disaster trends for at least 6 years after the event. However, the size of these surges is typically small vis-à-vis the estimates of the direct economic damages caused by the disasters.

4. **The Determinants of Post-Disaster Aid Surges.**

4.1 Model Specification

Having defined and quantified aid surges for a cross-section of countries in the last 40 years, we now exploit the variability in the data to try to explain the determinants of the size of these surges. The objective is to try to assess whether these aid surges are politically and/or strategically motivated, or whether the nature of the event and the resources available to the country are the primary drivers of donor's actions.

For that purpose we estimate regressions of the following type:

$$\Delta \ln Aid_{i,t} = \beta_0 + \beta_1 \ln Aid_{i,t-1} + \beta_2 \ln Intensity_{i,t} + \beta_3 \ln(1 + Media\ Coverage)_{i,t} + \beta_4 \ln GDP_{i,t-1} + \beta_5 \ln$$

The left hand side variable is the log difference between the average post disaster aid flows (up to two years after the disaster, including the disaster year itself) and the average aid flows in the two pre-disaster years.

When deciding on the control variables for the regressions we present in the next section, we rely on benchmark specifications on the determinants of aid, as used most recently in Werker et al. (2009) and Fink and Redaelli (2009). Our list of controls includes the following:

- $\ln Aid_{i,t-1}$: the natural logarithm of the initial pre-disaster aid level (average of two years preceding the event).
- $\ln Intensity_{i,t}$: either the natural logarithm of the reported amount of economic damages caused by the disaster(s) , or the number of people killed in the immediate aftermath of the event,
- $\ln(1 + Media\ Coverage)_{i,t}$: the natural logarithm of 1 plus media coverage of the disaster (proxied by the number of stories about it in the Associated Press within a six months period following the event), ,

- $\ln GDP_{i,t-1}$ the natural logarithm of the pre-disaster real GDP (US$ 2000),
- $\ln Pop_{i,t-1}$: the natural logarithm of the country's pre-disaster population.
- $\ln\left(\frac{Reserves}{GDP}\right)_{i,t-1}$: the natural logarithm of foreign exchange reserves (as percent of GDP),
- $Affinity_{i,t-1}$: political affinity index (based on the United Nations voting patterns).

More details on the variables and their sources are available in the appendix table 2.

4.2 Regression results

Our estimation results for the determinants of aid surges are presented in tables 2-4. Each table presents the same specifications for a different sample (samples 1, 2, and 3, respectively for tables 2, 3, and 4).[20] Since results are very similar, we will concentrate here on describing the estimated coefficients presented in table 2 (for sample 1 – our largest sample).

The R^2 for the specifications presented in table 2 is 0.24-0.3; with the smaller sample 3 actually having a better success with R^2 of 0.36-0.41 (table 4). While the explanatory power of our model is modest, this is in line with previous attempts to estimate the determinants of aid flows (e. g., Strömberg, 2007), and the literature documenting the excessive volatility of foreign aid.

In column 1, we report results of our benchmark specification. Our results indicate that, unsurprisingly, larger economic damage (destroyed infrastructure and other direct costs) will entail a larger aid surge. The same qualitative result holds when the magnitude of the disaster is measured by the number of people killed (see column 2).

[20] For definitions of the different samples, please see previous section.

In column 3 we examine another popular hypothesis regarding the determinants of the supply of aid – media exposure (e.g., Strömberg, 2007; and Drury et al., 2006). While media coverage does indeed seem to increase the amount of post-disaster aid, a close examination (see columns 4 and 5) reveals that this effect is largely due to the correlation between disaster impact (measured by either economic damages or fatalities) and media exposure. Once the size of the disaster is taken into account, the media coverage index is no longer statistically significant. Over the entire sample, the correlation between number of killed people and media coverage (in logs) is 0.61, whereas the same figure for media coverage and economic damages is 0.54. One reason why we do not find this media effect may be our narrower sample; restricted to truly large events. Small events are likely to generate little media attention, and little aid, thereby strengthening the statistical link between media exposure and aid flows in a more comprehensive sample.

One of our most robust results is that a higher initial (pre-disaster) aid level will lead to a lower aid surge. That suggests that donors may downgrade their disaster support to countries that they already support generously, or else they re-route previously donated aid streams for disaster support. This contradicts the 'boots-on-the-ground' hypothesis of Olsen et al. (2003)- that more aid will be given when there is the infrastructure to absorb it (if indeed we can consider previous average flow levels as representing the absorption capacity of the receiving country). This result is consistent throughout the specifications we estimate.

More intuitively appealing is our finding that countries with higher real GDP receive less in post-disaster aid, after controlling for the magnitude of the disaster. The aid literature has long observed that small countries tend to receive a larger per-capita share of aid. The same, however, is not true of population: the larger the population, the bigger is the aid surge that a country will receive. These two results, however, are clearly consistent with the observation that countries with higher per capita GDP will receive less aid.

The amount of foreign exchange reserves that a country possesses also seem to matter for the size of the post-disaster aid flow. In particular, a country with more reserves at its disposal will receive less in international assistance.

Finally, we include a measure of political affinity, since geo-political considerations are frequently mentioned in the literature on donor motivations in providing aid. However, this measure is never significant in our estimations, suggesting most likely a difficulty in measuring political interest when aggregating over several donor groups.

Table 3 and 4 present the same specifications as table 2, but for different sub-samples. Results are consistently similar for these smaller samples; though the statistical significance for some of the coefficients decreases. For example, the foreign reserves variable is no longer statistically significant by conventional measures, and the measured effect is smaller in absolute terms in table 3 than in table 2.

4.3 Robustness

The previous literature has suggested several other possible determinants of post-disaster emergency aid. In the regressions we present we do not include them, but we attempted to include them in specifications and the coefficients have always been indistinguishable from zero, suggesting either mismeasurement/misspecification or a lack of real correlation/causality. These variables were: (1) land Area (sq km, in logs) as another proxy for country size; (2) openness to international trade (total imports as percent of world total exports, in logs) since countries may possibly be more likely to assist trading partners in times of need; (3) a dummy variable indicating whether or not there is an armed conflict in the country inhibiting aid flows following the time of the disaster; (4) dummy variable for small island states since these generally receive proportionally more aid; (5) dummy variable for former colony status as the former colonial master may be more likely to assist; and (6) a dummy variables for the type of disaster as previous literature has found some intriguing differences in the reactions to different types of events.

Several other variables were not included since they reduced the sample significantly, and did not seem to add much explanatory power to the model. These were: sovereign debt as percentage of GDP, Polity IV's revised combined polity score measuring the political regime on an autocratic-democratic scale range, the International Country Risk Guide (ICRG) corruption index, the ICRG law and order index, and central government balance as percentage of GDP.

Overall, the results suggest that the main determinants of foreign aid in the aftermath of natural disasters are the intensity of the event itself and the recipient country's characteristics such as the level of development, country size and the stock of foreign reserves available. We do not find any evidence that political considerations or strategic behavior on the part of donors determine the size of the post disaster aid surges.

5. Conclusion and Future Research

In this paper, we estimated the size of aid inflows a developing country should expect following a large natural disaster. We provide estimates based on past disaster inflows, the characteristics of the disasters themselves, and other country-specific attributes. Our results indicate that realized post-disaster aid inflows are typically much smaller than headline numbers may indicate, and that they typically cover only a small fraction of estimated direct damages. We further find that damages are related positively to the subsequent aid inflows, but that higher incomes and higher incomes per capita, ceteris paribus, will mean less aid. More international reserves are also associated with less post-disaster aid being provided. We do not, however, confirm previous findings that aid inflows are also positively associated with media reporting and measures of political affinity and geo-strategic interests.

We view this as the 'opening shot' in a larger research effort to understand post-disaster reconstruction. The Scottish philosopher J. S. Mill observed, in 1872, that:

> "This perpetual consumption and reproduction of capital affords the explanation of what has so often excited wonder, the great rapidity with which countries recover from a state of devastation; the disappearance, in a short time, of all traces of the mischiefs done by earthquakes, floods, hurricanes, and the ravages of war. An enemy lays waste a country by fire and sword, and destroys or carries away nearly all the moveable wealth existing in it: all the inhabitants are ruined, and yet in a few years after, everything is much as it was before."
>
> (J. S. Mill (1872). *Principles of Political Economy,* p. 47)

Is this indeed the case? And in those cases in which a rapid recovery has indeed occurred, is it because of resources available in the domestic economy through domestic savings (as Mill thought)? What is the role of international assistance in this process?

In order to examine the effectiveness of the aid surge in mitigating the consequences of natural disasters, however, we first need to calculate these consequences. Only then can we correlate these with the size of the aid surge. Given the difficulties involved in identifying any statistically observable impact on national income, it may be more productive to look separately at each component of the national accounts (consumption, investment, government expenditures and the trade balance) and observe the way these are impacted by the post-disaster aid surge.[21]

A different set of questions, one that has not really been tackled in any comparative way (as far as we are aware), is to identify the most productive ways in which post-disaster aid should be disbursed (quickly as a lump-sum or sequenced over time). Observers have pointed out that large aid surges lead to higher prices and may therefore be less effective. Is this indeed the case? Should aid nevertheless concentrate on reconstructing as quickly as possible, in spite of the higher costs?

[21] For some discussion on the theoretical pitfalls for identifying long-term consequences of disasters, see Hallegatte and Przyluski (2010). For empirical difficulties, see Noy (2009) and Cavallo et al. (2010).

Table 1: Descriptive Statistics for Post-Disaster Surges

Event window: 2 years

Sample	Observations	Number of people killed	Killed per million of inhabitants	Economic Damages (2000 US$ millions)	Economic Damages (% of GDP)	Aid surge (2000 US$ millions)	Aid surge (% of GDP)	Coverage ratio (% of damages)	Aid surge (%)
Sample 1	138	327	59.8	258.7	4.2	7.3	0.100	2.9	18.1
Sample 2	79	303	52.9	249.3	4.2	13.7	0.192	5.3	23.5
Sample 3	94	235	71.5	295.3	4.2	8.3	0.139	3.3	18.5
Medians by decade (sample 1)									
1970	25	750	93.3	155.5	3.1	18.5	0.307	34.9	64.4
1980	37	250	61.2	180.5	5.5	12.2	0.316	1.9	9.3
1990	45	384	49.9	254.7	3.5	1.3	-0.093	0.3	1.9
2000	31	298	57.6	414.9	4.9	4.9	-0.010	3.4	17.6

Source: Authors' calculations based on EM-DAT and WDI datasets.

Table 2: Regression Results - Sample 1

Dependent variable: Aid Surge (logs)
Window: 2 years

Explanatory Variables	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)
Economic damage	0.0481			0.0343	
(US$ 2000 mn., in logs)	[2.55]**			[1.60]	
Number of people killed		0.0548			0.0389
(Total, logs)		[2.47]**			[1.63]
Media coverage			0.0466	0.0351	0.0329
(1 + number of reports in AP archive, in logs)			[2.32]**	[1.37]	[1.49]
Initial Aid level	-0.274	-0.228	-0.241	-0.283	-0.235
(average previous to event, in logs)	[-3.55]***	[-3.97]***	[-4.04]***	[-3.79]***	[-4.04]***
Real GDP	-0.187	-0.086	-0.123	-0.202	-0.111
(average previous to event, in logs)	[-3.06]***	[-2.02]**	[-2.53]**	[-3.39]***	[-2.33]**
Population	0.285	0.132	0.207	0.293	0.159
(average previous to event, in logs)	[3.41]***	[2.16]**	[3.38]***	[3.65]***	[2.40]**
International reserves over GDP	-0.0784	-0.071	-0.0825	-0.086	-0.0814
(average previous to event, in logs)	[-1.79]*	[-1.89]*	[-2.11]**	[-1.87]*	[-2.09]**
Political affinity index	0.522	0.123	0.231	0.46	0.17
(average previous to event, - 1 to 1)	[1.28]	[0.38]	[0.71]	[1.14]	[0.53]
Constant	1.039	0.967	0.92	1.345	1.181
	[1.91]*	[1.92]*	[1.82]*	[2.39]**	[2.26]**
Observations	86	109	109	86	109
R squared	0.284	0.24	0.24	0.3	0.256

t statistics in brackets
* p<0.10, ** p<0.05, *** p<0.01

Table 3: Regression Results - Sample 2

Dependent variable: Aid Surge (logs)					
Window: 2 years					
Explanatory Variables	**(3.1)**	**(3.2)**	**(3.3)**	**(3.4)**	**(3.5)**
Economic damage	0.0609			0.0555	
(US$ 2000 mn., in logs)	[1.96]*			[1.49]	
Number of people killed		0.0622			0.0505
(Total, logs)		[2.37]**			[1.73]*
Media coverage			0.0417	0.015	0.0239
(1 + number of reports in AP archive, in logs)			[1.59]	[0.46]	[0.83]
Initial Aid level	-0.276	-0.208	-0.224	-0.279	-0.21
(average previous to event, in logs)	[-2.40]**	[-2.35]**	[-2.28]**	[-2.32]**	[-2.26]**
Real GDP	-0.244	-0.0989	-0.124	-0.248	-0.115
(average previous to event, in logs)	[-3.03]***	[-1.71]*	[-1.82]*	[-3.08]***	[-1.79]*
Population	0.333	0.135	0.212	0.334	0.151
(average previous to event, in logs)	[2.69]**	[1.60]	[2.20]**	[2.65]**	[1.59]
International reserves over GDP	0.0269	-0.0153	-0.0278	0.0198	-0.0274
(average previous to event, in logs)	[0.32]	[-0.27]	[-0.46]	[0.22]	[-0.46]
Political affinity index	0.0604	-0.258	-0.176	0.0618	-0.226
(average previous to event, - 1 to 1)	[0.10]	[-0.57]	[-0.38]	[0.10]	[-0.49]
Constant	1.548	1.14	0.879	1.65	1.304
	[1.71]*	[1.58]	[1.26]	[1.84]*	[1.79]*
Observations	42	57	57	42	57
R squared	0.348	0.211	0.19	0.351	0.22

t statistics in brackets

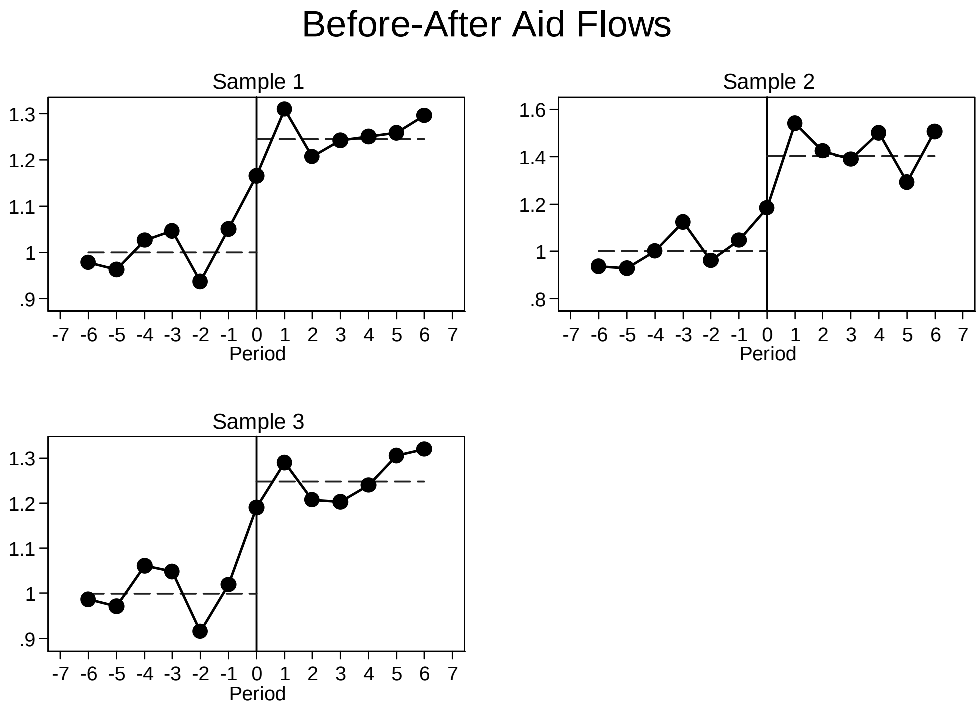
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Regression Results - Sample 3

Dependent variable: Aid Surge (logs) *Window: 2 years* **Explanatory Variables**	**(4.1)**	**(4.2)**	**(4.3)**	**(4.4)**	**(4.5)**
Economic damage	0.0668			0.0337	
(US$ 2000 mn., in logs)	[2.11]**			[0.78]	
Number of people killed		0.0687			0.0446
(Total, logs)		[3.16]***			[1.86]*
Media coverage			0.0622	0.0686	0.0468
(1 + number of reports in AP archive, in logs)			[3.20]***	[1.31]	[2.16]**
Initial Aid level	-0.197	-0.172	-0.197	-0.214	-0.186
(average previous to event, in logs)	[-1.98]*	[-3.48]***	[-3.69]***	[-1.95]*	[-3.64]***
Real GDP	-0.13	-0.033	-0.0721	-0.174	-0.0632
(average previous to event, in logs)	[-1.88]*	[-0.99]	[-1.81]*	[-2.21]**	[-1.62]
Population	0.23	0.0592	0.147	0.267	0.0957
(average previous to event, in logs)	[2.12]**	[1.08]	[2.78]***	[2.25]**	[1.60]
International reserves over GDP	-0.0312	-0.0962	-0.111	-0.0387	-0.109
(average previous to event, in logs)	[-0.61]	[-3.19]***	[-3.67]***	[-0.73]	[-3.71]***
Political affinity index	0.35	0.172	0.283	0.178	0.225
(average previous to event, - 1 to 1)	[0.50]	[0.50]	[0.84]	[0.24]	[0.67]
Constant	0.15	0.602	0.543	0.781	0.85
	[0.19]	[1.27]	[1.12]	[0.91]	[1.75]*
Observations	33	75	75	33	75
R squared	0.356	0.369	0.386	0.401	0.412

t statistics in brackets
* p<0.10, ** p<0.05, *** p<0.01

Figure 1: Before-After Aid Flows



Appendix Table 1: Disaster Data

Country name	Year	Number of people killed	Killed per million of inhabitants	Economic Damages (2000 US$ millions)	Economic Damages (% of GDP)	Aid surge (2000 US$ millions)	Aid surge (logs)	Aid surge (% of GDP)	Coverage ratio (% of damages)	Aid surge (%)
Nicaragua	1972	10,000	4,041.5	3,471.5	102.0	18.5	0.243	-0.14	0.53	27.45
Guatemala	1976	23,000	3,706.0	2,989.7	27.4	61.8	0.562	0.31	2.07	75.46
Honduras	1974	8,000	2,732.7	1,816.6	59.2	46.9	0.693	1.46	2.58	99.99
Honduras	1998	14,600	2,496.5	4,029.0	81.4	220.6	0.558	1.60	5.47	74.77
Sri Lanka	2004	35,405	1,846.6	1,199.1	7.0	208.2	0.326	0.52	17.36	38.55
Bangladesh	1991	139,252	1,204.3	2,438.3	6.4	-437.0	-0.229	-1.52	-17.92	-20.46
Solomon Is	1975	200	1,075.6	n.a.	n.a.	12.1	0.263	6.28	n.a.	30.04
Indonesia	2004	165,825	776.1	4,171.1	2.0	-320.1	-0.234	-0.28	-7.67	-20.89
Iran Islam Rep	1990	40,021	751.9	10,811.3	7.3	42.4	0.338	0.02	0.39	40.26
Iran Islam Rep	1978	25,045	707.6	128.6	0.1	56.3	0.905	0.05	43.76	147.28
Nicaragua	1998	3,332	687.1	1,049.0	29.2	2.0	0.003	-3.74	0.19	0.33
Haiti	2004	5,434	596.8	46.5	1.8	181.7	0.719	3.86	391.07	105.19
Vanuatu	1997	100	568.5	n.a.	n.a.	1.3	0.043	-2.27	n.a.	4.34
Dominica	1979	40	554.4	101.4	98.8	10.4	0.479	9.50	10.23	61.50
Ecuador	1987	5,002	535.7	2,265.6	14.5	18.7	0.089	0.75	0.83	9.29
Pakistan	2005	74,032	486.9	4,604.9	5.3	537.5	0.380	0.19	11.67	46.17
Papua New Guinea	1998	2,182	439.0	n.a.	n.a.	-20.4	-0.070	0.65	n.a.	-6.77
Bangladesh	1974	31,500	420.5	1,948.5	7.2	702.4	0.511	0.40	36.05	66.71
Iran Islam Rep	2003	26,797	405.9	491.8	0.4	2.3	0.019	-0.01	0.48	1.90
Grenada	2004	39	382.7	809.7	185.1	16.8	0.989	3.57	2.07	168.80
Solomon Is	1986	101	371.6	31.5	8.6	22.4	0.554	10.63	71.15	74.00
Bhutan	2000	200	366.9	n.a.	n.a.	4.9	0.083	-2.93	n.a.	8.61
Maldives	2004	102	358.6	428.2	67.9	14.6	0.461	2.11	3.42	58.50
Vanuatu	1987	48	355.1	37.8	21.1	12.2	0.281	11.85	32.29	32.47
St Lucia	1988	45	350.2	1,446.6	412.6	3.7	0.169	0.42	0.26	18.41
Somalia	1997	2,311	348.9	n.a.	n.a.	-24.8	-0.262	n.a.	n.a.	-23.02
Afghanistan	1998	7,053	322.5	21.2	n.a.	-39.1	-0.254	n.a.	-183.87	-22.41
Dominican Rep	1979	1,432	253.1	340.6	3.1	75.6	0.673	0.69	22.21	96.00
Vanuatu	1999	44	241.3	n.a.	n.a.	6.9	0.199	2.39	n.a.	22.03
Djibouti	1994	145	241.3	2.5	0.5	-27.8	-0.256	-3.80	-1128.95	-22.60
Yemen	1982	1,989	228.6	5,316.6	n.a.	-69.8	-0.085	n.a.	-1.31	-8.15
El Salvador	1986	1,100	220.0	2,363.7	39.5	61.6	0.137	1.71	2.61	14.71
El Salvador	2001	1,159	194.9	1,819.3	14.1	53.1	0.260	0.12	2.92	29.74
Solomon Is	1977	34	170.3	n.a.	n.a.	-11.3	-0.219	-7.14	n.a.	-19.69
Philippines	1976	6,405	152.4	938.7	2.1	-14.1	-0.028	-0.13	-1.50	-2.76

Bangladesh	1985	15,155	150.9	79.7	0.3	141.1	0.071	0.43	176.95	7.35
Algeria	1980	2,635	144.7	10,508.3	15.6	57.7	0.260	-0.06	0.55	29.70
St Lucia	1990	18	136.2	n.a.	n.a.	0.2	0.006	-1.56	n.a.	0.61
Mexico	1985	9,500	128.5	6,543.9	2.3	123.4	0.329	0.06	1.89	38.94
St Kitts and Nevis	1998	5	122.7	424.8	145.4	-1.5	-0.272	-1.03	-0.35	-23.79
Guatemala	2005	1,513	122.0	870.2	4.1	113.4	0.441	0.28	13.03	55.45
Belize	2001	30	120.1	246.1	30.0	-10.0	-0.458	-1.98	-4.07	-36.77
Oman	1977	107	111.1	n.a.	n.a.	57.8	0.229	0.72	n.a.	25.70
El Salvador	1982	520	109.8	500.4	8.1	153.8	0.543	3.50	30.73	72.15
Fiji	1973	59	108.8	n.a.	n.a.	11.0	0.211	-0.51	n.a.	23.55
Solomon Is	2007	52	107.0	n.a.	n.a.	-1.5	-0.011	-6.24	n.a.	-1.12
Philippines	1991	6,153	98.6	349.1	0.6	212.6	0.163	0.35	60.89	17.65
Cape Verde Is	1984	29	95.0	n.a.	n.a.	36.3	0.353	n.a.	n.a.	42.34
Comoros	1983	33	93.4	39.6	21.5	3.1	0.048	-0.48	7.91	4.93
Turkey	1976	3,846	93.3	74.7	0.0	182.6	0.895	0.14	244.33	144.62
Guatemala	1982	640	89.0	187.6	1.2	-13.2	-0.113	-0.15	-7.04	-10.72
Iran Islam Rep	1981	3,458	88.4	1,864.8	1.1	6.4	0.202	-0.01	0.34	22.43
Fiji	1979	53	87.1	n.a.	n.a.	1.0	0.015	-0.11	n.a.	1.50
El Salvador	1998	475	81.4	412.2	3.5	-86.1	-0.391	-1.26	-20.89	-32.36
Samoa	1991	13	80.6	351.2	248.1	9.8	0.224	10.18	2.78	25.13
Swaziland	1984	53	80.5	89.6	9.7	-2.8	-0.055	1.15	-3.08	-5.33
Honduras	1993	413	79.8	136.4	3.3	-10.9	-0.034	-0.89	-7.98	-3.34
Dominican Rep	2004	703	76.0	270.5	1.4	-39.6	-0.524	-0.18	-14.65	-40.76
Bhutan	1994	39	74.4	n.a.	n.a.	1.0	0.019	-0.99	n.a.	1.90
Algeria	2003	2,329	74.1	4,706.2	8.8	-47.5	-0.191	-0.14	-1.01	-17.39
Djibouti	1981	25	73.5	n.a.	n.a.	36.2	0.387	n.a.	n.a.	47.32
Tonga	1982	7	72.5	39.9	35.8	1.1	0.039	-2.62	2.82	3.98
Afghanistan	1991	1,347	72.5	75.8	n.a.	144.2	0.750	n.a.	190.23	111.64
Pakistan	1974	4,700	70.5	11.0	0.1	925.0	0.607	2.28	8447.05	83.50
Vanuatu	1985	9	69.8	275.9	127.6	1.0	0.021	4.50	0.35	2.17
Djibouti	2004	51	65.6	n.a.	n.a.	-8.1	-0.116	-1.21	n.a.	-10.98
Seychelles	1997	5	65.4	1.8	0.3	4.1	0.279	-0.15	222.27	32.18
Comoros	1987	24	61.2	13.6	5.5	-14.7	-0.247	-9.92	-108.50	-21.86
Kiribati	1972	3	60.3	n.a.	n.a.	10.0	0.567	-0.07	n.a.	76.27
Turkey	1975	2,385	59.3	53.4	0.0	58.4	0.271	0.03	109.36	31.14
Belize	2000	14	57.6	277.5	37.9	-7.7	-0.342	-2.01	-2.78	-28.95
Guinea	1983	275	56.4	n.a.	n.a.	-9.2	-0.049	-0.74	n.a.	-4.73
Philippines	1990	3,330	54.7	987.5	1.8	474.7	0.409	0.76	48.07	50.53
Mozambique	1971	500	52.9	n.a.	n.a.	0.2	0.497	n.a.	n.a.	64.37
Sri Lanka	1978	750	52.8	257.1	2.4	252.5	0.439	5.93	98.17	55.15
Nepal	1993	1,048	52.2	238.7	5.9	-61.9	-0.155	-1.86	-25.94	-14.34
Philippines	1984	2,679	51.3	556.9	1.0	209.1	0.258	0.84	37.54	29.47
Samoa	2005	9	50.3	n.a.	n.a.	4.4	0.162	-0.03	n.a.	17.60

Malawi	1991	472	49.9	30.3	1.3	23.3	0.045	0.57	76.98	4.56
Samoa	1990	8	49.9	260.2	182.7	16.9	0.429	18.25	6.50	53.57
Nepal	1981	750	49.8	n.a.	n.a.	76.8	0.260	0.32	n.a.	29.74
Viet Nam	1997	3,692	49.7	518.0	1.9	391.7	0.364	0.43	75.63	43.94
Cambodia	1994	506	47.2	n.a.	n.a.	123.5	0.402	1.18	n.a.	49.42
Mozambique	2000	832	46.8	420.2	9.4	487.6	0.445	11.12	116.04	56.00
Iran Islam Rep	1997	2,781	46.4	249.3	0.2	26.0	0.175	-0.01	10.41	19.16
Fiji	1985	32	45.9	121.2	6.5	-1.3	-0.021	0.25	-1.06	-2.09
Nepal	1988	806	45.3	86.8	2.0	79.6	0.170	1.40	91.67	18.52
Vanuatu	1972	4	45.1	n.a.	n.a.	16.4	0.619	n.a.	n.a.	85.64
Bolivia	1983	250	44.7	83.3	0.9	36.5	0.134	0.43	43.74	14.40
Guyana	2005	34	44.6	409.5	59.2	13.7	0.131	0.67	3.35	14.02
Gambia The	1999	53	43.7	n.a.	n.a.	7.7	0.187	1.28	n.a.	20.54
Nicaragua	1992	179	42.2	30.7	1.7	-77.9	-0.143	-19.59	-253.87	-13.33
Dominica	2001	3	42.1	n.a.	n.a.	8.9	0.554	3.12	n.a.	73.96
Dominican Rep	1998	347	41.3	2,104.4	10.1	39.6	0.423	0.10	1.88	52.70
Haiti	1980	220	39.5	808.3	n.a.	12.4	0.069	n.a.	1.54	7.19
Ecuador	1982	307	37.5	414.8	1.7	57.4	0.521	0.31	13.84	68.43
Somalia	2004	298	37.4	91.1	n.a.	31.3	0.184	n.a.	34.35	20.24
Nepal	1996	808	37.4	n.a.	n.a.	-1.3	-0.003	-2.01	n.a.	-0.34
Belize	1978	5	37.1	15.4	5.1	4.8	0.160	1.44	30.85	17.38
St Vincent and The Grenadines	2002	4	37.1	10.6	3.1	-1.4	-0.193	-0.12	-13.62	-17.53
Guatemala	1998	384	36.7	794.4	4.2	42.3	0.173	0.04	5.32	18.92
Seychelles	2004	3	36.2	27.3	4.3	1.5	0.164	0.25	5.34	17.86
Nicaragua	2007	198	35.8	n.a.	n.a.	-40.4	-0.072	-1.89	n.a.	-6.95
Bangladesh	2007	5,505	35.4	1,990.6	3.9	243.3	0.218	0.32	12.22	24.39
Honduras	1982	130	34.7	180.5	3.6	160.7	0.663	2.81	89.05	93.99
Nicaragua	1988	130	33.5	578.6	10.4	95.9	0.370	17.13	16.58	44.82
Indonesia	2006	7,248	33.1	2,801.8	1.1	-248.7	-0.228	-0.19	-8.87	-20.42
Afghanistan	1982	500	32.5	1.8	0.0	-24.1	-0.882	n.a.	-1351.27	-58.60
Bangladesh	1988	3,506	32.4	3,091.3	9.0	-72.1	-0.035	-0.48	-2.33	-3.42
Afghanistan	1992	614	32.3	4.9	n.a.	-87.5	-0.378	n.a.	-1783.41	-31.50
Fiji	1997	25	32.2	29.1	1.3	-3.6	-0.090	-0.18	-12.20	-8.60
Colombia	1999	1,229	32.0	1,921.7	1.9	96.5	0.431	0.14	5.02	53.91
Antigua and Barbuda	1989	2	31.6	110.6	23.6	-2.9	-0.390	-0.85	-2.62	-32.30
Tonga	1973	3	30.8	1.9	n.a.	3.3	0.567	n.a.	172.72	76.35
Algeria	2001	921	30.2	295.3	0.5	83.3	0.411	0.12	28.23	50.90
Antigua and Barbuda	1995	2	30.1	453.8	80.0	-0.6	-0.154	-0.09	-0.12	-14.29
Morocco	1995	791	29.8	10.2	0.0	-165.5	-0.297	-0.82	-1620.46	-25.67
Fiji	1980	18	29.0	4.6	0.2	2.5	0.039	-0.03	55.54	3.96
Philippines	1972	1,088	28.9	1,101.0	3.6	384.4	0.858	0.96	34.92	135.84
St Lucia	1994	4	28.6	n.a.	n.a.	13.1	0.332	1.47	n.a.	39.34
Fiji	1993	21	28.4	119.3	6.5	-10.9	-0.202	-0.95	-9.15	-18.28

Honduras	1994	151	28.4	n.a.	n.a.	-30.9	-0.096	-1.08	n.a.	-9.11
Fiji	1986	20	28.2	55.8	3.1	0.9	0.014	1.01	1.55	1.41
Philippines	1981	1,352	28.1	217.8	0.4	157.6	0.254	0.13	72.36	28.92
Turkey	1983	1,346	27.9	43.0	0.0	-688.4	-0.982	-0.59	-1599.19	-62.54
St Vincent and The Grenadines	1992	3	27.8	n.a.	n.a.	-3.3	-0.204	-1.83	n.a.	-18.41
Antigua and Barbuda	1998	2	27.8	106.2	17.2	5.1	0.819	0.84	4.76	126.93
Mozambique	1977	303	27.8	155.5	n.a.	101.7	0.726	n.a.	65.41	106.67
Cambodia	2000	347	27.7	160.0	4.5	135.3	0.370	1.56	84.56	44.80
Dominica	2007	2	27.6	16.5	6.3	-1.9	-0.118	-0.70	-11.73	-11.13
Dominica	1995	2	27.6	221.2	90.5	12.4	0.621	5.57	5.60	86.15
Papua New Guinea	2007	172	27.4	n.a.	n.a.	-7.6	-0.040	-0.82	n.a.	-3.96
Antigua and Barbuda	1999	2	27.1	n.a.	n.a.	2.1	0.275	0.28	n.a.	31.69
Dominica	1984	2	27.0	3.3	2.5	2.2	0.082	-2.72	65.83	8.55
Turkey	1971	935	25.8	21.2	0.0	-149.7	-0.237	-0.31	-704.75	-21.10
Korea Dem P Rep	2007	610	25.8	247.4	n.a.	44.1	0.639	n.a.	17.81	89.54
Vanuatu	1993	4	25.2	7.2	3.1	-8.1	-0.207	-4.95	-113.80	-18.67
Philippines	1995	1,725	25.2	1,155.4	1.6	-423.6	-0.436	-1.14	-36.66	-35.35

Note: We drop nine events of our sample because these coincided with another major event in the country that was more likely to have affected foreign aid. Dropped events are Afghanistan (2002) – war in Afghanistan, Bangladesh (1973) – Post Independence process, Haiti (1994) – UN political intervention after 1991 coup d'état , Iran (1972) – Several military conflicts, aid flows dropped by almost 70%, Saint Lucia (1980) – Saint Lucia's independence from United Kingdom , Turkey (1999) – historically low levels of aid (after disaster's aid-flows increased by almost 500%), Venezuela (1999) – historically low levels of aid in 1997 (aid after disaster increased by almost 200%).

Source: Authors' calculations based on EM-DAT and WDI datasets.

Appendix Table 2: Data Sources

Variable	Source	Notes
ODA total net disbursements	OECD DAC Database. Available at http://stats.oecd.org/	US$ 2000 millions
Economic damage	EM-DAT Database. Available at http://www.emdat.be/database	US$ 2000 millions
Number of people killed	EM-DAT Database. Available at http://www.emdat.be/database	Total
Media coverage	Associated Press Archive. Available at http://www.aparchive.com/	Number of reports
Real GDP	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	US$ 2000 dollars
Population	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Total
International reserves over GDP	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Ratio
Political affinity index	The Affinity Of Nations Index database (Version 4.0). Available at http://dss.ucsd.edu/~egartzke/htmlpages/data.html	Average with DAC countries, -1 (low affinity) to 1 (high affinity)
Land area	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Squared kilometers
Openness to international trade	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Percent. Author's calculations.
Armed conflict dummy	UCDP PRIO Armed Conflict Dataset. Available at http://www.prio.no/CSCW/Datasets/	Author's calculations
Small island state dummy	United Nations. Available at http://www.un.org/special-rep/ohrlls/sid/list.htm	
Former colony dummy	Correlates of War. Available at http://www.correlatesofwar.org/	Author's calculations
Type of disaster dummy	EM-DAT Database. Available at http://www.emdat.be/database	Author's calculations
Sovereign debt as percentage of GDP	Ugo Panizza debt dataset. Avaiable at http://sites.google.com/site/md4stata/linked/public-debt	Author's calculations
Polity IV's revised combined polity score	Polity IV project. Available at http://www.systemicpeace.org/inscr/inscr.htm	-10 (autocracy) to 10 (democracy)
ICRG corruption index	International Country Risk Guide dataset. Available at http://www.prsgroup.com/ICRG.aspx	0 (high corruption) to 6 (low corruption)
ICRG law and order index	International Country Risk Guide dataset. Available at http://www.prsgroup.com/ICRG.aspx	0 (low law and order) to 6 (high law and order)
Central government balance as percentage of GDP	World Economic Outlook dataset.	Percent

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